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Real-Time Analysis of Online Product Reviews by Means of Multi-Layer Feed-Forward Neural Networks

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ABSTRACT

In the recent past, the quantitative analysis of online product reviews (OPRs) has become a popular manifestation of marketing intelligence activities focusing on products that are frequently subject to electronic word-of-mouth (eWOM). Typical elements of OPRs are overall star ratings, product attribute scores, recommendations, pros and cons, and free texts. The first three elements are of particular interest because they provide an aggregate view of reviewers' opinions about the products of interest. However, the significance of individual product attributes in the overall evaluation process can vary in the course of time. Accordingly, ad hoc analyses of OPRs that have been downloaded at a certain point in time are of limited value for dynamic eWOM monitoring because of their snapshot character. On the other hand, opinion platforms can increase the meaningfulness of the OPRs posted there and, therewith, the usefulness of the platform as a whole, by directing eWOM activities to those product attributes that really matter at present. This paper therefore introduces a neural network-based approach that allows the dynamic tracking of the influence the posted scores of product attributes have on the overall star ratings of the concerning products. By using an elasticity measure, this approach supports the identification of those attributes that tend to lose or gain significance in the product evaluation process over time. The usability of this approach is demonstrated using real OPR data on digital cameras and hotels.

Key words: eWOM, feed-forward neural network, online product reviews, real-time analysis.
JEL Classification: M31, C45, C55.
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1.0 INTRODUCTION AND EXISTING LITERATURE

In the "Web 2.0", users interact with other users by producing content, usually referred to as "user-generated content" (Dhar and Chang, 2009), that might be interesting for the Web community. In blogs, discussion groups, chat rooms, online forums and opinion platforms, users express and share their opinions and experiences on a wide range of topics, including products (e.g., digital cameras), services(e.g., those provided by hotels) and sellers (e.g., online retailers). One special type of user-

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generated content, namely online product reviews (OPRs), plays an increasingly important role in everyday purchasing decisions of consumers, and, therewith, also influences the way retailers and service providers run their businesses. An international survey conducted in 2010 by Harvard Business Review Analytic Services that included more than 2,000 companies revealed that nearly a quarter of the organisations surveyed are using review sites/discussion forums as a source of information, and 29% report collecting and tracking customer reviews on their own website or other websites (HBRAS, 2010). Together with the literature reviewed in the following studies of this type suggest the conclusion that OPRs are more and more used to complete traditional market research and monitoring in a complementary way in order to achieve a higher level of marketing intelligence. According to (Morabito,2014, p. 68) marketing intelligence based on social listening techniques can help to create and sustain a competitive advantage in terms of products and services differentiation. In the present context "social listening" means listening to what consumers are talking about on the web, e.g. in order to direct the interest of other consumers to a certain product or to advise against it. The information and recommendations provided in this manner are often referred to as electronic word-of-mouth (eWOM) in marketing literature.

OPRs are composed of positive, negative and/or neutral statements or evaluations typically made by previous or potential customers about products, services or sellers. Today, OPRs exist for almost any consumer product or service, from books, coffee and pharmaceuticals to consumer electronics and vacation trips (Puri, 2007; Sen and Lerman, 2007). To simplify notation, we subsume physical products (e.g., digital cameras or books) and services (e.g., those provided by hotels or airlines) under the term "product" in this paper. OPRs provide sellers with important information on customer satisfaction and the popularity of competitors' products. They are also useful for identifying consumer preferences and thus can give businesses new insights into what customers like or dislike (Decker and Trusov, 2010). Compared with seller-created product information, OPRs are more user-oriented and canhelp consumers to find products matching their own personal preferences (Chen and Xie, 2008). By using OPR data, marketing researchers are able to directly investigate the relationships between eWOM and product sales in different industries (Li and Hitt, 2010). Furthermore, there is an increasing amount of literature on the helpfulness of OPRs in purchase decision-making as well as their economic impact within the context of sales predictions. A recent study on these topics by (Ghose and Ipeirotis,2011) shows that certain characteristics of reviews, such as subjectivity and readability, affect product sales. (Lee and Shin,2014) recently examined how the quality of OPRs affects the acceptance of the reviews, as well as the evaluation of the sources and how such effects vary depending on the product type.

An essential feature of opinion platforms motivating consumers to visit these sites is their helpfulness and, directly related to this, their up-to-date nature or topicality (Liu et al., 2008). Particularly in the case of technological products, such as Blue ray or DVD players, notebooks, digital cameras or smart phones, the product attributes that matter most in the purchasing process may change over time due to successive technological improvements and modifications. In the case of smart phones, for example, the product attribute "resolution "of the integrated camera is likely to be a permanent topic in OPRs due to continuously increasing demands regarding the achievable image quality. In contrast to this, the relevance of "battery life" in the course of time is less predictable due to the fact that, on the one hand, lithium-ion technology has enabled the provision of high-quality batteries, whereas, on the other hand, the multifunctional of modern smart phones is demanding ever higher standards regarding energy supply.

A completely different situation, but with more or less the same implication, can be observed with hotel booking or reservation platforms (Jones and Chen, 2011). In 2004, OPRs posted on *Tripadvisor.com* provided customer ratings for the predefined hotel attributes "value", "rooms", "cleanliness" and "service". Today, the attributes "location" and "sleep quality" are available in addition to the previous ones. The problem with providing information (in this case, customer ratings) about he right attributes become seven more obvious if *Tripadvisor*'s set of attributes is compared to those of other popular platforms offering the same or similar services: *HRS.com*, for instance, currently presents scores for 14 attributes, ranging from "cleanliness" and "room equipment" to "breakfast" and the "staff's willingness to serve". *Booking.com*, on the other hand, uses six attributes ("clean", "comfort", "location", "facilities", "staff" and "value for money"). Already the differences regarding the number of product attributes being presented and the different spectrum of attributes underlines the importance of a continuous monitoring of the influence the rated attributes have on the overall evaluations, e.g. in the form of overall star ratings or recommendations.

In the case of almost steadily arriving new OPRs, the dynamically changing database hampers the efficient estimation of standard econometric response functions. This might be one reason for the rare analysis of the time dependence of the sensitivity of overall evaluations to variations of product attribute scores in the course of time. The present paper is intended to contribute to the bridging of this gap in OPR-related research. Furthermore, statistical modelling requires assumptions regarding the exact function to be used. In contrast to this, multi-layer feed-forward neural networks, sometimes also called multilayer perceptrons, are highly flexible in this respect, and are therefore considered a promising option for the data analysis problem at hand.

In their frequently cited paper (Hornik et al.,1989) show that multi-layer feed-forward neural networks with one hidden layer using arbitrary squashing functions can be used to "approximate any Borel measurable function to any desired degree of accuracy, provided sufficiently many hidden units are available. In this sense, multi-layer feed-forward networks is a class of universal approximators". The neural network approach considered in the following not only allows the implicit response function to change over time, but also enables an adaptive model calibration. The latter means that, in the ideal case, each new OPR induces a further parameter adaptation, i.e., an updating of the weights used to represent the strengths of the connections between the units in the neural network. In software packages like IBM SPSS Neural Networks 22 this procedure is called "online training". In doing so, the neural network can take into account changing significances of the product attributes of interest. It is even argued that "online training is superior to batch for 'larger' datasets with associated predictors; that is, if there are many records and many inputs, and their values are not independent of each other, then online training can more quickly obtain a reasonable answer than batch training" (IBM Corporation, 2013). More general discussions of relevant issues in data stream mining – the methodological field the current problem can be attributed to– can be found, for instance, in (Gaber et al.,2010), (Gama and Rodriguez,2009),(Pramod and Vyas,2013), and (Gaber et al.,2014).

Real-time analyses of user-generated content are also a topic of recent research in opinion mining and sentiment analysis. (Zhang et al.,2012), for example, put a focus on real-time helpfulness predictions based on voter opinions and, among others, introduce a probabilistic framework that allows an efficient processing of incoming data and provides reliable helpfulness predictions. The power of the suggested algorithms is demonstrated using anonymous voter opinions crawled from user-generated reviews posted on *Amazon.com*.(Aston et al.,2014a) recently introduced the so-called modified balanced winnow algorithm for sentiment analysis on online social networks. Using three real-world network datasets they demonstrate how this approach can be used to detect and dynamically track the importance of features in data streams. Similar work can be found in the paper by (Aston et al.,2014b)who made use of the perceptron algorithm for sentiment analysis on *Twitter* data streams. (Zimmermann et al.,2013) investigated the problem of monitoring sentiments in product reviews and proposed a stream mining method that learns opinionated product features from streams of product reviews. All in all, recent literature shows that the real-time analysis of consumer opinions posted online is not only a comparatively new but also a very challenging topic in quantitative marketing research. Despite the very promising approaches in sentiment analysis the comprehensive empirical analysis of the time-dependent variation of product attributes' impact on the overall product evaluation in OPRs is still in its infancy. Against this background, the present paper strives to contribute to a better understanding of the dynamics of product attribute scores in OPRs.

The remainder of this paper is organised as follows: Section 2 briefly specifies the dynamic data generation process and the multi-layer feed-forward neural network approach suggested to track the influence product attribute scores have on the overall star ratings of the products over time. Section 3 will then present two prototypical applications of the new approach by focusing on real OPR data on digital cameras and hotels. Section 4 concludes the paper by discussing limitations of the suggested approach and providing an outlook on promising extensions or improvements.

2.0 DATA AND METHODOLOGY

2.01 TRANSFORMING OPR POSTINGS INTO DATA STREAMS

Before being able to dynamically analyse OPRs in the above-indicated way, a database has to be generated that automatically grows when a new review is added to the OPR platform to be monitored. To solve this database generation problem web crawlers, also known as spiders or robots, like the open source web crawler for Java called*crawler4j*can be considered (for a deeper discussion of the web crawler issue see, e.g.,(Raghavan and Garcia-Molina,2001) or, more recently,(Bhushan and Kumar,2012). After having adjusted the web crawler to the OPR platform of interest and after having specified the product category to be examined, the crawler can extract the required data with a predefined frequency that fits the monitoring task (e.g., every hour) and store the relevant elements in the database.

Figure 1 shows a typical OPR (top) and its formal html coding (bottom) as provided by *Epinions.com*. The blue and red elements of the html code correspond with the natural language text. The red elements would define one dataset or “observation” in the database needed for the intended dynamic OPR analysis. In the present case, we would have 4 (orange) stars for the overall product evaluation, 4 scores for product attribute “ease of use”, 5 scores for “durability”, 3 scores for “battery life”, 4 scores for “photo quality”, and 3 scores for “shutter lag”. The mentioned attribute scores and the overall star rating (together with the free text and the pros and cons) have caused the reviewer to recommend the product. With the date included to identify the OPRs posted since the last access, the resulting dataset or “observation” can be written as:

[star_rating = 4, ease_of_use = 4, durability = 5, battery_life = 3, photo_quality = 4, shutter_lag = 3, date = “2011-06-10”]

Figure 1. Exemplary OPR and its formal html coding (Source: Epinions.com)


Read all 10 Reviews | Write a Review

Canon EOS 5D Mark II Body OOnly Digital Camera

Written: Jun 10 '11

User Rating: Excellent

Ease of Use:
Durability:
Battery Life:
Photo Quality:
Shutter Lag

Pros: Features such as color change and anti shake are incredibly useful.

Cons: This camera is a little expensive but very worth it!

This is an amazing product. Not only is it digital, but the zoom and other extras such as changing the colors of pictures are incredibly wanted. I have used this camera so many times and to be completely honest I've dropped it a few times as well. This camera is vertually indestructable. I can't imagine life without it. The zoom is amazing and it is an attractive camera on top of everything. This camera is very easy to use. All ages could use it with easy pictures on buttons explaining how to uses said buttons.

Recommended: Yes

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<div id="single_review_area"><div><h1 class="summary title_gray" style="margin-bottom:5px;">Canon EOS 5D Mark II Body OOnly Digital Camera</h1><span
class="iReviewStarsMedYellow medStars40 rating“><span class="value-title" title="4"></span></span><span class='dtreviewed rgr'>Written:
Jun 10 '11<span class="value-title" title="2011-06-10"></span></span></div><div class="review_details"><ul class="user_review_chart"><li><span
style="display:inline-block; float:left;"><span class="rgr" style="display:inline-block; font-weight:bold; margin:0 5px 5px 0;">User Rating: </span><span
class="rgr">Excellent</span></span></li><li><span class="rgr“>Ease of Use:</span><span><img
src="http://img.epinions.com/images/epi_images/e3/quant_4.gif" width=80 height=11></span></li><li><span class="rgr">Durability:</span><span><img
src="http://img.epinions.com/images/epi_images/e3/quant_5.gif" width=80 height=11></span></li><li><span class="rgr">Battery Life:</span><span><img
src="http://img.epinions.com/images/epi_images/e3/quant_3.gif" width=80 height=11></span></li><li><span class="rgr">Photo Quality:</span><span><img
src="http://img.epinions.com/images/epi_images/e3/quant_4.gif" width=80 height=11></span></li><li><span class="rgr">Shutter Lag:</span><span><img
src="http://img.epinions.com/images/epi_images/e3/quant_3.gif" width=80 height=11></span></li></ul><div class="user_review_summary"><span
style="display:inline-block; margin-bottom:3px;"><b style="display:inline-block; margin-right:5px;">Pros:</b>Features such as color change and anti shake are
incredibly useful.<br /></span><span style="display:inline-block; margin-bottom:3px;"><b style="display:inline-block; margin-right:5px;">Cons:</b>This camera is a
little expensive but very worth it!<br /></span></div></div><div class="user_review_full"><p class="description plot_details"> This is an amazing product. Not
only is it digital, but the zoom and other extras such as changing the colors of pictures are incredibly wanted. I have used this camera so many times and to be
completely honest I've dropped it a few times as well. This camera is vertually indestructable. I can't imagine life without it. The zoom is amazing and it is an
attractive camera on top of everything. This camera is very easy to use. All ages could use it with easy pictures on buttons explaining how to uses said buttons.<br />
<br> <b>Recommended:</b>Yes
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In the present case, each dataset would consist of seven variables with either numerical or string values (the latter has to be transformed into numerical ones). The date can be transformed, e.g., into UNIX standard time format, which would result, for example, in 1307664000 if the posting took place exactly at midnight. By using a more formal notation and by assuming a virtually unlimited number *R* of reviews arriving for the product category of interest, the dynamically growing database has the structure shown in Table 1. In the following, the index *r*(with $r = 1, \ldots, R, \ldots$) refers to the arriving OPRs, which cause the neural network to carry out further adaptations. In order to ensure an adequate training of the neural network, it is assumed that R is large enough.

Table 1.Possible structure of the successively growing OPR database

OPR (no. or index)	*Overall star rating*	*attribute score 1*	*attribute score 2*	…	*attribute score A*	*Date* (e.g., UNIX)
1	y_1	x_{11}	x_{12}	…	x_{1A}	*11071…*
⋮	⋮	⋮	⋮	…	⋮	⋮
r	y_r	x_{r1}	x_{r2}	…	x_{rA}	12266…
⋮	⋮	⋮	⋮	…	⋮	⋮
R	y_R	x_{R1}	x_{R2}	…	x_{RA}	13582…
⋮	⋮	⋮	⋮	…	⋮	⋮

2.02 THE OPR-NN APPROACH

As already motivated in Section 1 a 3-layer feed-forward neural network promises maximum flexibility regarding the analysis task at hand. Therefore, the following methodological consideration makes use of this architecture with one output unit that represents the evaluation variable.Since theoverall evaluation of a product is mostly represented by astar rating we will focus on this in the following as well. Alternatively, the use a binary recommendation variable representing the posted "yes" or "no" (see Figure 1) is possible.The suggested implementation for dynamic OPR analysis makes use of the following notation:

A Number of input units (=number of product attributes considered)
H Number of unitsin the hidden layer
x_{ra} Score or rating of the *a*-th ($a = 1, \ldots, A$)product attribute in adaptation step*r*(corresponding to OPR*r*)
y_r Overall star rating in adaptation step *r* (resulting fromOPR*r*)
θ_{ha} Weight of the link connecting input unit*a* with hidden unit*h*
η_h Weight of the link connecting hidden unit*h* with the output unit

Furthermore, two parameters are needed to control the network adaptation process. The first one, the so-called learning rate ω_1, should be chosen between 0.1 and 0.3 and accounts for the strength of the weight adaptation following the arrival of a new OPRto the database. The higher ω_1 is, the more sensitive the neural network reacts to a newly arrived OPR and the faster the neural network "learns" this new information. The second parameter, called momentum ω_2, influences the convergence speed of the neural network. The higher it is, the less the current weights of the neural network are adapted to a newly arrived OPR. Values between 0.8 and 0.9 are considered useful here (Hertz et al., 1991).A further discussion of suitable values for ω_1 and ω_2 can be found, e.g., in (Yu and Chen,1997). The basic function of the suggested OPR-NN approach thenreads as follows:

$$y_r^{NN} = f(\boldsymbol{\theta}, \boldsymbol{\eta}; \mathbf{x}_r) = \left(1 + \exp\left(-\left(\sum_{h=1}^{H} \eta_h \left(1 + \exp\left(-\left(\sum_{a=1}^{A} \theta_{ha} x_{ra} + \theta_{h,A+1}\right)\right)\right)^{-1} + \eta_{H+1}\right)\right)\right)^{-1}, \quad (1)$$

with $\boldsymbol{\theta}$ and $\boldsymbol{\eta}$ representing the vectors of unknown weights of the neural network and $\mathbf{x}_r$ representing the observed values of the independentinput variables (i.e.,product attributes) resulting from OPR *r*. The so-called bias weights $\theta_{h,A+1}, \ldots, \theta_{H,A+1}$ and η_{H+1} resemble the intercepts known from regression analysisand account for variations in the output variable that cannot be attributed to the input variables. The number *H*of unitsin the hidden layer has a significant effect on the network's capability of finding the best function to represent the interesting relationship (Hornik et al., 1989), but it also involves the danger of over-fitting in the case of having been chosen too large. Therefore, applications of the suggested OPR-NNapproach should start with one hidden unit, the most parsimonious 3-layer configuration in the present context. If the data representation quality proves insufficient, then a step-by-step enlargement of the hidden layer and, therewith, the parameterisation of the neural network as a whole should be tried.In contrast to this, dropping all hidden units, i.e. doing without a hidden layer,in favour of parsimony regarding the network weights to be adapted and instead directly linking the input units (for the product attribute scores) to the output unit (for the overall star rating) leads to an network architecture that corresponds to thepopular logistic regression approach (Bentz and Merunka, 2000; Dreiseitl andOhno-Machado,2003):

$$y_r^{NN} = f(\boldsymbol{\theta};\mathbf{x}_r) = \left(1+\exp\left(-\left(\sum_{a=1}^{A}\theta_a x_{ra} + \theta_{A+1}\right)\right)\right)^{-1}. \tag{2}$$

A popular technique that can be used to determine the *H*·(*A*+2)+1weights $\theta_{11},\ldots,\theta_{HA};\theta_{1,A+1},\ldots,\theta_{H,A+1}$ and $\eta_1,\ldots,\eta_H;\eta_{H+1}$ of the 3-layer architecture is the so-called back propagation algorithm, introduced by Rumelhart et al. in 1986 (Rumelhart and McClelland, 1986;Ripley, 1996). In the present context a newly arrived OPR *r* causes the following data processing steps (assuming that the neural network has already been trained using the preceding *r* – 1 OPRs):

1. Use the weights $\theta_{11}(r-1),\ldots,\theta_{H,A+1}(r-1),\eta_1(r-1),\ldots,\eta_{H+1}(r-1)$ resulting from the adaptation of the neural network to the last (i.e., (*r* – 1)-th) OPR.
2. Estimate the overall star rating as a function of the weights and the product attribute scores(cf. Table 1) observed with OPR *r*: $y_r^{NN} = f(\boldsymbol{\theta}(r-1),\boldsymbol{\eta}(r-1);\mathbf{x}_r^{obs})$.
3. Compute the error $err_r = \left(y_r^{obs} - y_r^{NN}\right)^2$ coming along with the network's adaptation to OPR *r*(where y_r^{obs} refers to the star rating observed with OPR *r*).
4. Compute back propagation variables $\Delta\theta_{ha}(r)$ and $\Delta\eta_h(r)$ for OPR *r* with:
   $\Delta\theta_{ha}(r) = \omega_2\Delta\theta_{ha}(r-1) - \omega_1\dfrac{\partial err_r}{\partial\theta_{ha}(r-1)}\quad\forall a,h$ and $\Delta\eta_h(r) = \omega_2\Delta\eta_h(r-1) - \omega_1\dfrac{\partial err_r}{\partial\eta_h(r-1)}\quad\forall h$
5. Update the network weights:
   $\theta_{ha}(r) = \theta_{ha}(r-1) + \Delta\theta_{ha}(r)\ \forall a,h$ and $\eta_h(r) = \eta_h(r-1) + \Delta\eta_h(r)\ \forall h$
6. Return to step 1 when the next OPR arrives and repeat adaptation steps 2 to 5.

In the last two and a half decades, several further developments and improvements of the original back propagation algorithm have been published. However, since the focus of this paper is on the dissemination of the basic idea of dynamic OPR analysis, we do not further emphasise this point and instead refer to the corresponding literature (see, e.g., Leonard and Cramer,1990;Torvik and Wilamowski, 1993;andAnastasiadis et al., 2005).Furthermore, a selection of software tools for implementingmulti-layer feed-forward neural networks and multi-layer perceptrons, respectively,such as *Numap 7*,are available from the*IPNNL* platform at the University of Texas at Arlington. Other tools like*IBM SPSS Neural Networks 22*,*EasyNN plus*, *NeuroSolutions for Excel* or *MLP/X 5.0* for Windows applications are available from the developers' websites. There are flexible free-of-charge access to neural network tools such as *nnet* and *neuralnet*is providedin the popular R environment for statistical computing. The *neuralnet* implementation of the back propagation algorithm by (Günther and Fritsch,2010, p. 32) ignores the momentum term (corresponding to $\omega_2 = 0$ in the above specification), but assumes the learning rate ω_1 to depend on the current iteration *r* "in order to speed up convergence in shallow areas".

2.03 SENSITIVITY ANALYSIS USING A SPECIFIC ELASTICITY MEASURE

The above OPR-NN approach builds aflexible bridge between the scores of individual product attributes and the overall star rating of the product as a whole. However, substantial interpretations of the network weights are less intuitive and become the more cumbersome, the more units and, therewith, the more connections or weights are considered. In order to facilitate the interpretation of the neural network, or, to be more precise, its weights, elasticity measure can be computed (see, e.g., Trusov et al.,2009) for an often-cited study using elasticities in the eWOM context). Along these lines, the following measure describes the sensitivity of the overall star rating y_r to marginal changes (i.e., for $\Delta \to 0$) of product attribute score x_{ra} after the processing of OPR *r*:

$$elast_{y_r;x_{ra}}^{NN} = \frac{x_{ra} \cdot \; f(\boldsymbol{\theta},\boldsymbol{\eta};x_{r1},\ldots,x_{ra}+\Delta,\ldots,x_{rA}) - f(\boldsymbol{\theta},\boldsymbol{\eta};x_{r1},\ldots,x_{ra}-\Delta,\ldots,x_{rA})}{2\cdot\Delta\cdot f(\boldsymbol{\theta},\boldsymbol{\eta};x_{r1},\ldots,x_{ra},\ldots,x_{rA})} \qquad a=1,\ldots,A \qquad (3)$$

According to usual interpretations in business management, $elast_{y_r;x_{ra}}^{NN}$ quantifies the sensitivity of the overall star rating to changes of the score of product attribute *a*. The less changes of product attribute score influence the overall star rating, the more the above elasticity measure approaches zero. Product attributes with elasticity values equal to zero are insignificant for itsrealisation and the explanation of the overall product evaluation. They could therefore be removed from the OPR platform or replaced by another product attribute that can be assumed to matter more in the present sense.To check for this kind of sensitivity in a more strategic way, moving averages $ma_{y_r;x_{ra}} = \frac{1}{n}\; elast_{y_r;x_{ra}}^{NN} + elast_{y_{r-1};x_{r-1,a}}^{NN} + \ldots + elast_{y_{r-(n-1)};x_{r-(n-1),a}}^{NN}$ of elasticity values(with $n > 1$) for the attributes $a = 1,\ldots,A$ can be computed and graphically visualised.The use of moving averages instead of individual elasticity valuessmoothout temporary and, thus, not really mattering structural changes of the attribute effects. In our study a quarter-wise averaging of the elasticities proved appropriate, but month-wise or even week- and day-wise averaging might also be adequate if the data gives rise to the suspicion of greater dynamics.

3.0 EMPIRICAL APPLICATIONS OF THE OPR-NN APPROACH

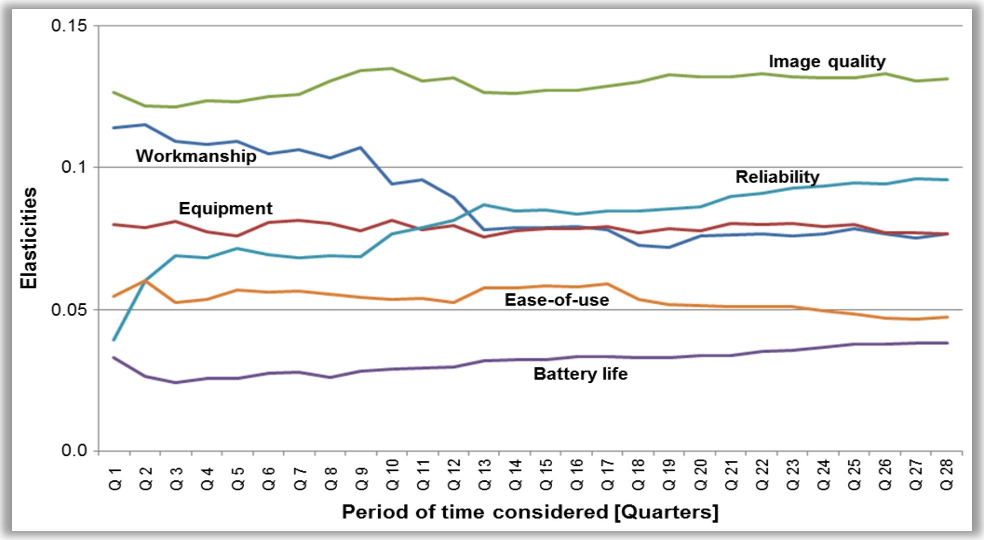
In the following, theabove approachwill be applied to OPR data on digital cameras and hotels. Both datasets cover several years and, therewith, allow sensitivity analyses of the interesting type. In the digicam dataset, we observe about 2.7 OPRs per day on average, whereas the corresponding value for the hotel data equals 95.0. The comparatively large number in the second case, among others, results from the fact that leading hotel booking or reservation platformsusually coversa wide spectrum of hotels, which inevitably leads to high posting frequencies.

3.01 APPLICATION TO OPR DATA ON DIGITAL CAMERAS

The databaseconsidered firstcontainsabout 7.000 OPRs. Each of these OPRsfeaturesa star rating of the digicamreviewed as well as six product attribute scores (for “workmanship”, “equipment”, “image quality”, “battery life”, “reliability” and “ease-of-use”) and a timestamp. All scores are based ona 5-point scale and are normalised to values between 0.2 (if the attribute was assigned 1 star) and 1.0 (in the case of 5 stars) for technical reasons.Several neural networkarchitectures implemented in SPSS and R weretestedto run sensitivity analyses of the interesting type.The results provided by a 3-layer architecture and those provided by a 2-layer architecture proved quite similar regarding the detected elasticity patterns. Therefore, and in order to keep the methodology as simple as possible, the 2-layer solution with a quarter-wise averaging procedure is used in the following. The resulting smoothed elasticity curvesare presented in Figure 2.

The presented curves provide a couple of interesting findings: firstly, all elasticity values show the expected positive sign throughout the whole period of time considered. However, the sensitivity of the overall star rating to the product attributes at hand differs significantly regarding its extent and is characterised by different dynamics. The attribute “workmanship” tendentially loses its influence, which, at least partly, can be explained by the generally increased and meanwhile high quality of modern digital cameras in general.A converse development can be observed for the attribute “reliability”. The nearly continuously increasing sensitivity of the overall star rating concerning this attribute can be explained, among others, by the fact that the basic digital camera technologies nowadays show a degree of maturity that, in principle, guarantees an acceptable level of reliability. But exactly this also implies that disappointed expectations may cause consumers to express their displeasure by writing online reviews which lead to bad overall evaluations. So, the higher the general level of reliability, the more sensitive the overall evaluation is to low scorings in this respect. A weak increase of sensibility can also be diagnosed for the attribute “image quality” which might correspond with its increasing importance from a product development perspective.

Figure 2. Smoothed elasticity curves for the digicam data



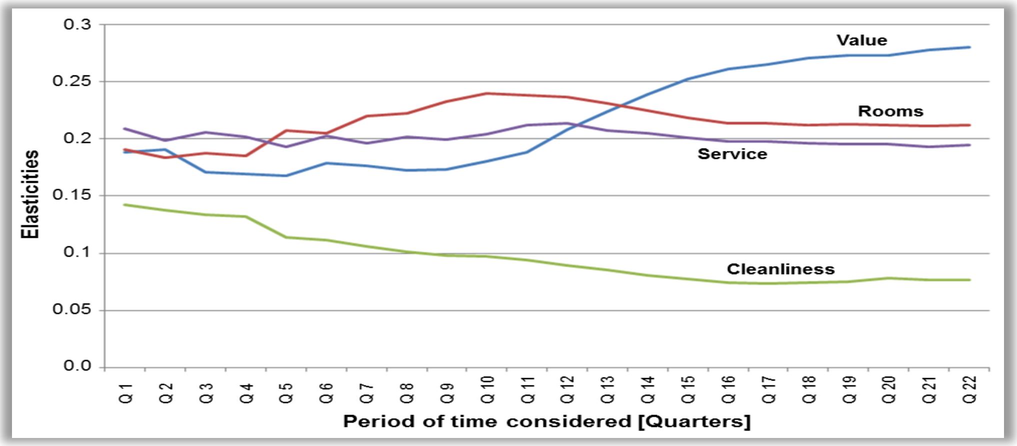
A closer look at the digital camera market teaches us that from the year 2000 to the year 2014 the resolution, which can be assumed to determine image quality to a large extent, has increased from about 2 mega-pixels to about 24 mega-pixels. The sensitivity of the overall star rating to the attributes “equipment” does not change in the considered period of time, whereas “ease-of-use” seemingly tend to lose influence, albeit on a comparatively low level. Finally, “battery life” obviouslyplayeda less influential role in the period of time considered. The corresponding elasticity values are predominantly close to zero with a weak upward trend. For the latter two attributes one might ask the question whether theseattributes willbe helpful in the future as anchor points of opinion tracking at all.

3.02 APPLICATION TO OPR DATA ON HOTELS

In order to further verify the suitability of the suggested approach for dynamicsensitivity analyses, we will now have a look at a second database generated fromabout190.400 OPRson hotels. Each of these OPRs features an overall star rating as well as four hotel attribute scores (for “value”, “rooms”, “cleanliness”,and “service”) and a timestamp. The results of an OPR-NN approach-based sensitivity analysis of this data are presented in Figure 3.

Once again, all elasticity values show the expected positive sign and vary over time, partly even to a greater extent than in the digicamexample. The strongest change is found with the attribute “value”, which seemingly has become more influential in the recent past. The opposite is true for “cleanliness”. This, to some extent, might be a consequence of increasing standards concerning this feature resulting from the increasing transparency of a hotel’s quality because of the popularity of hotel booking platforms. Participating in such a platform and neglecting cleanliness at the same time is counterproductive. Accordingly, the more cleanliness is beyond question for the concerning hotels, the less it impacts the overall star rating. All in all, the detected patterns show that all four attributes have an effect on the overall evaluation and thus contribute to its explanation, though at different levels. Due to the large amount of data underlying these patterns, the deviation of the attribute-specific elasticity values from zero can be considered significant.

Figure 3.Smoothed elasticity curves for the hotel data



This suggests the conclusion that it makes sense to maintainall four attributes as possible anchor points of customer opinion tracking, although the necessity of "cleanliness" needs closer surveillance in the near future.

4.0 CONCLUSIONS AND OUTLOOK

This paper introduced a new approach based on the principles of multilayer perceptrons which allows a dynamic tracking of the influence the scoresof important product attributes have on the overall star rating of the concerning product or service. By means of a specific elasticity measure, the approach supports the identification of those attributes that tend to lose or gain significance in online product or service evaluation processes. The basic usability and potential of this approach for marketing intelligence was demonstrated using real OPR data on digital cameras and hotels.

Besides these methodological aspects our research has considerable managerial implications as well: First of all, it shows how important a continuous monitoring of OPRs is. Snapshot-like analyses can only draw an incomplete pictureof the underlying evaluation process and may even cause misleading conclusions aboutwhat currently matters on the part of the customers. Secondly, the understandingof how the impact of interesting product attributes develops in the course of time can help to allocate the available resources more efficiently, e.g. in hotel management or new product development. Thirdly, comparisons of the dynamic patterns detected in different product categoriesbeing discussed online by using the same or similar product attributesmay help to learn more about the volatility of the strength of effects. This is of particular interest with respect tomore general product attributes like "reliability", "value" or "ease-of-use".Finally, the results of dynamic OPR analysis can help opinion platforms to increase the meaningfulness of the reviews posted there and, therewith, the usefulness of the platform as a whole, by directing eWOMor reviewing activities to those product attributes that really matter at present.

Although the presented results indicate the advantageousness of using neural network techniques for the monitoring task at hand,our approach leaves room for several improvements. First of all, focusing on the overallstar ratings as the crystallisation of consumers' overall product assessments may only tell half the story. However, extending the analyses to the recommendations or non-recommendations often included in online reviews(see Figure 1) would imply a new understanding of sensitivity measurement which, usually, requires metric or at least quasi-metric data as assumed in the case of ratings or scores of the above type. The typical "yes/no" coding of recommendations does not allow a straightforward application of the suggested OPR-NN approach. Secondly, an important issue in neural network-based data analysis is the determination of the optimal number of units in the hidden layer. This point becomes even more challenging in the context of data streams, where the complexity of the patterns to be represented can change overtime. Thirdly, the adequate use of neural networks requires special methodical expertise which, if missing on the part of a potential user, might hamper the execution of monitoring analyses of the presented type. Limiting the methodology to 2-layer architectures counteracts the two problems mentioned last to some degree. Finally, more general implications regarding the usefulness of this new type of OPR analysis require more tests that include further product or service categories.

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